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A new typology of climate change risk for European cities and regions: Principles and applications

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ABSTRACT

This paper aims to contribute to the analysis of climate change risk through the development of a new spatially-explicit typology of climate risk for European cities and regions. In doing so, it offers a direct response to the Intergovernmental Panel on Climate Change (IPCC) call to advance awareness of climate change risks at sub-national levels through the integration of hazard, exposure and vulnerability domains into a composite risk classification that covers the whole of Europe. K-means clustering was applied to 49 variables at NUTS3 level where the final classification resulted in an upper-tier of eight 'classes', which were subsequently partitioned to derive a lower-tier of 31 'sub-classes'. A three-stage analysis of the eight-fold class configuration was then undertaken focusing on the distribution of climate risk classes, raising significant issues to inform climate change adaptation planning policy, practice and research. The analysis revealed an uneven distribution of climate change risk across the 33 countries covered by the typology, reinforcing the IPCC message that adapting and building resilience to climate change risk is not a 'one-size-fits-all' exercise. In the second stage, the analysis focused on determining whether there was a difference in the climate change risk facing different settlement types in Europe. The analysis revealed the extent of variation in the climate change risk characteristics of Europe's urban and rural areas, revealing the potential for *peri*-urban areas to fall between climate change risk agendas or priorities when compared to urban–rural contexts. The final component of our analysis considered the extent to which climate change risk classes exhibit patterns of spatial clustering. Here we found that climate change risk exhibits evidence of spatial clustering but the extent of the clustering varies between different classes as the relationship between contiguous NUTS3 regions changes. This finding has notable implications for transboundary adaptation planning where discontinuities in political buy-in, competition, resourcing and awareness of risk could serve to undermine the coherence and adequacy of policy responses at a time when greater cooperation and alignment is needed.

1. Introduction

This paper reports on the development of a new and novel analysis of climate risk for European cities and regions, drawing on research undertaken as part of the European funded Horizon 2020 RESIN project.[1] Europe's climate is changing. Projections point towards shifts in temperature and precipitation over the coming decades alongside an increasing incidence of extreme events such as floods and heat waves (Intergovernmental Panel on Climate Change (IPCC), 2022). In response, the European Commission's strategy on adaptation to climate change calls for a strengthening of adaptation planning and associated risk assessments (European Commission, 2021). These changes are emerging against a backdrop of widespread recognition that the magnitude of the societal shifts associated with a transition to a low carbon economy to (potentially) offset the severest climate change impacts need to coincide with "…challengingly deep and rapid mitigation" (Millar et al., 2017: 741).

Risk sits as the foundation of climate change adaptation activity. In its 5th Assessment Report (AR5) published in 2014, the IPCC transitioned from a vulnerability to a risk-based conception of climate change

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[1] The typology and data are accessible through the European Environment Agency 'data products' portal and an open-source online portal [https://european-crt.org/index.html].

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adaptation and mitigation (Burkett et al., 2014) to align the climate change community with those practicing in disaster risk management (Connelly et al., 2018). Between AR5 and AR6 (IPCC, 2022), the concept of risk has evolved to ensure more consistent application across the IPCC's three working groups (Reisinger et al., 2020: 4). The domains of hazard, exposure and vulnerability remain consistent between AR5 and AR6 as the core elements that determine the nature and extent of climate risk. However, the evolved definition makes it clearer that risk refers to the impacts of climate change as well as human responses to climate change, with further guidance given on characterising uncertainty and the precise application of terminologies in risk assessments (Reisinger et al. 2020).

As such, AR6 has further consolidated the IPCC focus on climate change risk. As the vision statement preceding the 6th Assessment Report (AR6) demonstrates, the risk-based perspective has assumed prominence in the IPCC approach to assessments of climate change and its focus on promoting effective long-term adaptation solutions (Chair of the IPCC, 2017). In the vision statement for AR6, it is recognised that urban areas and regions will play key roles in realising the goals of the Paris Agreement but that there is a

> "…need to advance the understanding of climate change risks at sub-national levels, as well as the opportunities and impediments to adaptation action" (Chair of the IPCC, 2017: 26-7).

The novel contribution of this research is in its direct response to the IPCC call to advance awareness of climate change risks at sub-national levels (also see Carter et al., 2015). This is achieved through the development of a new spatially-explicit typology of climate change risk with a focus on European cities and regions, with climate risk typologies identified as having the potential to support adaptation to climate change (Carter et al., 2015). As such, the typology was developed to reflect climate change risk in European cities and regions and their underlying physical infrastructures through the integration of hazard, exposure and vulnerability domains into a *composite* typology for Europe.[2] Through its design, the typology is positioned to offer a *relative* as opposed to *absolute* measure of climate change risk. This decision reflected two main concerns. The first was to ensure that the typology was developed using standardised metrics so that meaningful comparison between European cities and regions could be undertaken to aid knowledge and practice sharing. The second was awareness that insurance and credit agencies may interpret risk differentially, either capitalising risk into their models or cascading financial burdens onto governments and individuals (Mills, 2005). Minimising, for ethical reasons, the categorisation of certain cities and regions as more or less risky than others was therefore an important consideration in developing the typology (see Klein, 2009).

Overall, this approach distinguishes the climate risk typology from other European-scale, spatially oriented classifications, and decision-support tools, which focus on climate change adaptation and resilience but tend to consider risk in absolute terms, assess distinct domains or pathways of the IPCC's risk framework, or privileged exemplar cities. These include the European Environment Agency's Urban Vulnerability Map Book (EEA, 2016), ESPON's Climate project (ESPON Climate, 2011; ESPON Climate, 2022), the European funded RAMSES project involving a climate risk impact analysis for a selection of European cities (Tapia et al., 2015), and the IPCC's own climate scenario interactive data atlas of climate hazards linked to projected future scenarios (Iturbide et al. 2021).

Having reported on the development of the typology, the paper offers an analysis of the spatial and structural dimensions of climate change risk as expressed through the new typology, responding directly to the IPCC's call for further research in understanding the structural and spatial dimensions of climate change risk at sub-national level (Chair of the IPCC, 2017). In the next section, we offer a conceptualisation of climate change risk that underpins the European Climate Risk Typology (ECRT), before exploring in more detail the methodologies employed to develop and analyse the typology. The final section discusses the research findings and suggests avenues to further develop the typology and explore its potential applications.

1.1. *Conceptualising climate change risk*

The starting point for the conceptualisation underpinning the ECRT is the IPCC's risk-based framework. The IPCC contend that climate change risk results from the interaction of climate *hazards* with *exposure* and *vulnerability* to these hazards, where *vulnerability* is separated into *sensitivity* and *adaptive capacity* (IPCC 2014) (see Fig. 1 for definitions).

Climate change risk is inherently uncertain and spills across scales, administrative boundaries, and sectors (Adger et al., 2018; Landauer et al., 2019). At the same time, data on climate change risk is often patchy; where user-friendly, open-source data platforms designed to assist practitioners in translating climate risk information into action, remain somewhat limited (Connelly et al., 2018; Ye et al., 2021). This has led to the IPCC to suggest that to support climate risk assessments, scientific effort should be directed towards "…improving spatial resolution within regions and reducing uncertainties when filling knowledge and data gaps" (Chair of the IPCC, 2017: 7).

Our contribution lies in the development of a European-wide and spatially-explicit climate risk typology as a novel approach to representing the climate change risk characteristics of European cities and regions and (some of) their physical infrastructures. In doing so, we adopt a conceptualisation of cities and regions as complex systems where they are conceived as a configuration of "….interacting subsystems or elements" exhibiting multiple interconnections and interdependencies that cut across sectors, and spatial and temporal scales (Batty 2009: 1042). From this starting point, cities and regions represent a 'system of systems' where social-ecological systems are impacted and shaped by *multiple drivers of change*, conveniently categorised by Loveridge (2002) into six broad themes: social, technological, environmental, economic, political, and values (STEEPV). These drivers of change and their manifold intersections are understood to influence how cities and regions contribute to climate change, how they are affected by it, and ultimately how they respond to related threats and opportunities (Grimm et al., 2008).

Climate change hazards interact with other drivers of change that influence city and regional systems, and tracing these multiple interconnections and cascading non-linear implications is therefore challenging (Adger et al., 2018). Related hazards and longer-term shifts in the climate, including floods, droughts and heat waves, generate physical (e.g., damage to infrastructure) and socio-economic (e.g., loss of business revenue) impacts on urban and regional systems. Although extreme events are of particular concern due to the magnitude of impacts they can generate (IPCC, 2012), incremental changes to the climate or a sequence of less severe events can nevertheless pose major challenges to city and regional systems going forward. Therefore, the nature of climate change risks depend on how vulnerable exposed 'receptors' (e.g., people, infrastructure) are to a hazard event or gradual changes in the climate. The sensitivity or susceptibility of receptors to hazards needs considering in relation to their capacity to cope with the impacts that might arise (Connelly et al., 2015). Unsurprisingly then, vulnerability intersects with socio-economic structures and the political and institutional characteristics of a place, which includes the willingness to address climate change, or the strategic capacity to develop adaptation responses (including financial, technical and human resource capacities) (IPCC, 2014; Castán Broto, 2017, Young and Essex,

[2] The RAMSES project (FP7 2012–17) developed risk assessment tools using existing data, identifying climate risks for 571 European cities as contained in the Urban Audit. However, the RAMSES approach did not cover the whole of Europe and was more limited in its selection of indicators than the approach outlined here (Connelly et al., 2018).

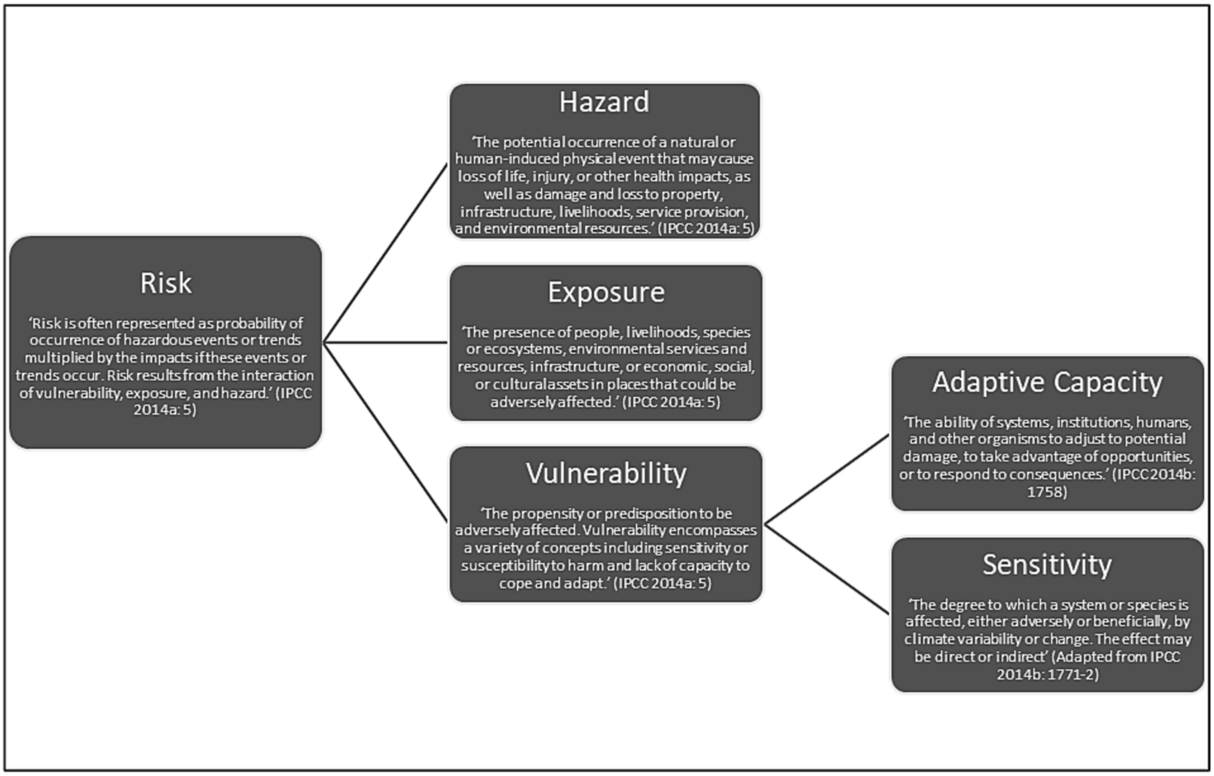

Fig. 1. IPCC AR5 climate change risk approach.

2020).

Recognising then that risks are generated when climate hazards (and other drivers of change) interact with features of urban and regional systems, it follows that the severity of climate risks is influenced by the receptor being exposed to a hazard and the extent to which the receptor is vulnerable to harm or damage from a hazard event if it occurs (Dickson et al., 2012, IPCC, 2014). Climate risk frameworks, such as the one championed by the IPCC, typically recognise that a given system can be vulnerable – as vulnerability is an inherent property of the system – yet it is not until the system is exposed to a hazard that the risk is manifested (Gallopín, 2006; IPCC, 2014). Likewise, a system might be exposed to a hazard, but if sensitivity to that hazard is low and/or adaptive capacity is high, the level of risk may be mitigated.

The ECRT presented here is an attempt to develop a *composite* classification of climate change risk that recognises the trade-offs and interactions of climate hazards, exposure, and components of vulnerability. It does so at a regional scale across Europe in a way that seeks to contribute to 'hot spot' mapping of climate change risk through a data-driven framework (see de Sherbinin, 2014; de Sherbinin et al., 2019). The ECRT was developed with the ambition of helping end-users better describe and analyse the elements of the city and regional system that influence climate risk and to support the evidencing, assessment and communication of climate change risk facing Europe's cities and regions (see also Solecki et al., 2015; de Sherbinin et al., 2019; ESPON Climate, 2022). In structuring the analysis of the ECRT in this paper, four research questions are considered:

1. What are the characteristics of climate change risk in Europe's cities and regions?
2. How is climate change risk distributed across Europe?
3. What are the differences in climate change risk facing different settlement types in Europe?
4. To what extent do different types of climate change risk cluster spatially across Europe?

The next section reports on the methodology used to develop the ECRT.

2. Methodology

The methodology consists of three stages and was developed using conventions that ensure consistency with established approaches for developing area-based classifications.

2.1. Stage 1: Data collection and indicator development

The first step in developing the ECRT involved reviewing existing academic, policy and grey literature on climate risk and its constituent elements (hazard, exposure, sensitivity, and adaptive capacity). Web of Science and Scopus were used to identify peer reviewed papers that discussed risk and vulnerability assessments across a range of climate related hazards. The gathered literature assisted in the understanding of conceptual issues relating to the operationalisation of vulnerability, and related terms, in addition to identifying suitable indicators (see Appendix A for the approach).

Having identified dominant themes within the literature, the next step involved reviewing and auditing data from a variety of European (e.g., EUROSTAT; Joint Research Council) and international (e.g., NASA; Open Street Map) data repositories. The review was undertaken to identify the availability and quality of potential indicators across the four climate risk domains that underpin the ECRT, and to determine their spatial and temporal coverage. Alongside the systematic review, early stages of the typology development work involved three rounds of workshop-based consultation with RESIN project partners that focused on: 1) defining the role of the ECRT; 2) methodological development; and 3) future output and applications (see Appendix B).

Based on the review and consultation work, it was decided to develop the ECRT at NUTS3 level of which there are 1379 NUTS3 regions (at the time of the research). NUTS3 is a population-based classification system, where each NUTS3 unit contains between 150,000 –

800,000 people. As a result, the density of NUTS3 regions across Europe varies substantially. For example, there are 402 NUTS3 units in Germany compared to 21 in Sweden and just one in Cyprus.

The decision to focus the ECRT at the NUTS3 scale was taken for several reasons. Firstly, there is a wide availability and coverage of European data at the NUTS3 scale needed in developing climate risk indicators. Second, NUTS3 regions cover continental Europe unlike other potential units such as the Urban Atlas, offering the potential for the development of a climate change risk typology with comprehensive coverage of Europe. Third, NUTS3 regions have been subject to a further classification that segments each unit based on whether they exhibit land-use and population characteristics that are consistent with the region being *predominantly urban, intermediate,* or *predominantly rural* in nature. This meant that cities as well as *peri*-urban hinterlands and rural areas could be considered separately in more detailed analysis of climate change risk using an official EU classification of NUTS3 regions (e.g. Mortoja and Yigitcanlar, 2020).

Candidate risk indicators, covering the domains of hazard, exposure, sensitivity, and adaptive capacity, were identified through assessment of existing indicators or by determining options for generating new indicators. Two assessment criteria underpinned the choice of candidate indicators: *conceptual relevance* and *technical robustness* (Wong and Watkins, 2009):

Conceptual relevance:

- Indicator is consistent with the conceptual risk themes, underpinning the domains of hazard, exposure, sensitivity, and adaptive capacity, as identified through the literature review.

Technical robustness:

- Availability: available at the chosen spatial unit (i.e., NUTS3) or it must be available at a scale that allows aggregation to the chosen unit.
- Consistency: clarity in definition and ability to compare across spatial units, potentially over time.
- Transparency: clearly stated specifics as to why the indicator was originally collected and how.
- Continuity: agreed and stated methodologies and routine data collection to enable continuity in the methods and measures used.
- Relevance: intelligence has to be reliable and relevant to the issue concerned.
- Time series: has an appropriate timeframe for measuring the issue of concern.

Some of the hazard indicators were derived from open-source repositories and/or derived using GIS analysis (e.g., flood risk). Other hazard variables, notably the climate projection indicators, were developed by Fondazione Centro EuroMediterraneo sui Cambiamenti Climatici (Fondazione CMCC) as part of the RESIN project. These climate change indicators were derived through climate simulations consisting of eighteen GCM-RCM combinations over the European domain (EURO-CORDEX) with resolution 0.11 degree (~12 km) (see Appendix C for the RCM specifications).

As an initial starting point, the simulations considered were obtained according to the IPCC scenarios RCP4.5 (intermediate emissions) and RCP8.5 (high emissions) set against a contemporary control period of 1981–2010.

- RCP 4.5 – this is a stabilization scenario where technological change, and the implementation of greenhouse gas emissions reduction strategies lead to a future where the most severe impacts of climate change become less likely.
- RCP 8.5 – this climate change scenario reflects major shifts in temperature and precipitation patterns, and is driven by increasing emissions, high population growth and limited technological innovation.

The climate anomalies were evaluated over the future period 2036–2065 with respect to the control period 1981–2010. To generate the climate variables, the following steps were undertaken (Fondazione CMCC, 2019):

1. Evaluation of the annual mean values of the indicators for the control period 1981–2010[3] and the future period 2036–2065 for all EURO-CORDEX simulations by using daily climate variables (maximum temperature, minimum temperature, mean temperature, precipitation)
2. Calculation of the anomalies of each climate indicator, as difference between the temporal mean value of the indicator in the future period 2036–2065 and in the control period 1981–2010 covering the European continent, excluding Turkey.
3. Determination, for each climate indicator, of the anomaly multi-model ensemble using the native model horizontal resolution. The multi-model ensemble is calculated as the mean value of results of all models.
4. For each climate indicator, calculation of the spatial mean value of the anomaly multi-model ensemble over all European NUTS3 regions was carried out using an area-weighted average of all overlapping model grid points falling in each NUTS3 region.

The initial starting point for the EURO-CORDEX hazard indicators was to include the baseline (control period) in the ECRT to reflect the near contemporary hazard context alongside RCP 4.5 and RCP 8.5 to reflect hazard futures. However, analysis of the baseline and derived scenarios revealed excessive correlations (0.79 to 0.99, $p < .000$) between the equivalent indicators (e.g., mean temperature) of the baseline and the modelled scenarios under RCP 4.5 and RCP 8.5 assumptions at NUTS3 level. As such, it was decided to only retain the RCP 8.5 indicators as the worst-case scenario in developing the ECRT on the basis that the retained RCP 8.5 indicators were statistically correlated to the near contemporary baseline and underlying trends modelled in RCP 4.5 (see *Stage 2* for details on the process of handling indicator redundancy).

The exposure, sensitivity, and adaptive capacity indicators were either available from open-source repositories (e.g., EUROSTAT) or were generated, typically through combining separate variables into a single composite indicator or using geoprocessing operations in GIS. Details of the conceptual principles and methods underlying the development and assessment of the final adopted indicators can be found in the supplementary information (Appendix D).

It is important to acknowledge the trade-offs underlying the development of the ECRT. Data coverage and quality is inconsistent across European countries, creating notable challenges in monitoring climate change risk (Connelly et al., 2018). The indicator audit revealed a lack of consistency in spatial indicator coverage across NUTS3 regions that required the use of techniques such as interpolation as part of a strategy of estimating missing data. Likewise, the temporal coverage of indicators varied, with some indicators being collected regularly and others irregularly or as snapshots. Furthermore, other indicators were only available as projections. This challenge has been recognised by others who have highlighted limitations in having to conceptually retrofit indicators to the IPCC risk framework (Connelly et al., 2018), the

[3] At the time the hazard indicators were commissioned (i.e., 2016) and the typology was developed in 2017/18, the 1981–2010 control period represented a near contemporaneous baseline for present-day hazards, from which the simulations were derived. Not all hazard indicators included a control period from which RCP 4.5 and 8.5 scenarios were produced and so for some hazard indicators proxy indicators drawing on historic or contemporary periods were adopted instead.

analytical constraints imposed by sub-standard data (Chair of the IPCC, 2017), and the interpretive risks associated with constrained data availability at resolutions that could be inappropriate for certain evidence-based analyses and planning functions (ESPON Climate, 2022). This has led to calls for a commitment to continuous monitoring and data collection to ensure the reliability and robustness of indicators going forward (ESPON Climate, 2022). While acknowledging these limitations and constraints, the approach reported here follows a robust and technically-informed contribution to climate hot-spot analysis and represents a demonstration of what is possible given the availability and coverage of current data. Many of the indicators in Table 1 were developed or compiled specifcally for the purpose of creating the ECRT and represent a valuable resource in their own right. Against this backdrop, we hope the research serves to support the ESPON Climate (2022: 58) call for greater attention to be paid to "continuous monitoring and data acquisition at appropriate scale" to help improve the reliability and robustness of assessments of climate related risks going forward.

2.2. Stage 2: Data preparation

Overall, 79 potential indicators covering hazard, exposure, sensitivity, and adaptive capacity were initially identified through the audit process. Following consultation with partners and stakeholders and initial exploratory data analysis, 67 indicators were retained for further analysis and/or development. Working conceptualisations, definitions and metadata descriptors were developed for each of the 67 retained indicators outlining the conceptual underpinnings of the indicator and its technical specifications.

The first task in processing the data was to identify, correct or remove error-laden values (e.g., due to the incorrect recording of values during the processing of the original data). It was also necessary to identify and record extreme outliers in the indicators early in the process of developing the typology. Many statistical procedures assume a normal distribution in the sample of data being subject to analysis. To overcome problems of non-normal distributions, each indicator was assessed using *Skewness* (a measure of the symmetry of a frequency distribution) and *Kurtosis* (a measure of the peakedness of the data). The Shapiro-Wilks Test for normality was also applied as a way of statistically testing for non-normal distributions. Transformation and standardisation procedures (see below) were used to address non-normal distributions, identified based on the Shapiro-Wilks Test, and/or where skewness or kurtosis values exceeded $+1$ or -1.

The initial analysis revealed that all the variables suffered from skewness and/or kurtosis and so would benefit from transformation/standardisation. Combinations of four transformation functions (Log; Box-Cox; Inverse Hyperbolic Sine; Fractional rank and inverse distribution) and three standardisation approaches (Z-score, range, and interdecile range standardisation) were tested, resulting in 12 new datasets, that were subjected to further examination of outliers, skewness, and kurtosis values (see Gale et al., 2016). Following iterative testing and pilot cluster runs (see step 3), a combination of fractional ranking and inverse distribution transformation and range standardisation was adopted, following their use elsewhere in typology development (Hincks et al., 2018).

To address missing data, areal interpolation was adopted where necessary. Areal interpolation is a geostatistical interpolation technique that extends kriging theory to normally distributed data averaged over polygons (see Logan et al., 2014). The technique enables predictions and standard errors to be made for all points within and between the input polygons (i.e., NUTS3 units). The aggregation of polygonal data is a two-step process. First, a smooth prediction surface for individual points is created from the source polygons, interpreted as a density surface. This prediction surface can then be re-aggregated to target polygons (i.e., NUTS3 units). This two-step process can be used to predict and subsequently impute values for polygons where data is missing. The

Table 1
Climate change risk variables.

Indicator Name	IPCC AR5 Risk Domain	Radial Chart Ref.
Mean Temperature (RCP 8.5)	Hazard	V1
Summer Days (RCP 8.5)	Hazard	V2
Ice Days (RCP 8.5)	Hazard	V3
Heat Waves (RCP 8.5)	Hazard	V4
Consecutive Dry Days (RCP 8.5)	Hazard	V5
Consecutive Wet Days (RCP 8.5)	Hazard	V6
Heavy Precipitation Days (RCP 8.5)	Hazard	V7
Very Heavy Precipitation Days (RCP 8.5)	Hazard	V8
Coastal Hazards	Hazard	V9
Drought Hazard	Hazard	V10
Wildfires	Hazard	V11
Fluvial Hazard	Hazard	V12
Landslide Hazard	Hazard	V13
Population in settlements exposed to fluvial flooding	Exposure	V14
Road infrastructure exposed to fluvial flooding	Exposure	V15
Rail network exposed to fluvial flooding	Exposure	V16
Transport nodes exposed to fluvial flooding	Exposure	V17
Population in settlements exposed to coastal hazards	Exposure	V18
Road infrastructure exposed to coastal hazards	Exposure	V19
Rail network exposed to coastal hazards	Exposure	V20
Transport nodes exposed to coastal hazards	Exposure	V21
Population in settlements exposed to landslide	Exposure	V22
Road infrastructure exposed to landslide	Exposure	V23
Rail network exposed to landslide	Exposure	V24
Transport nodes exposed to landslide	Exposure	V25
Length of major road networks (km^2 per NUTS3 region)	Vulnerability – Adaptive Capacity	V26
Length of railway network (km^2 per NUTS3 region)	Vulnerability – Adaptive Capacity	V27
Density of major road intersections	Vulnerability – Adaptive Capacity	V28
Density of transport nodes	Vulnerability – Adaptive Capacity	V29
Airports per head of the population	Vulnerability – Adaptive Capacity	V30
Ports per head of the population	Vulnerability – Adaptive Capacity	V31
Hospital sites per head of the population	Vulnerability – Adaptive Capacity	V32
Number of powerplants per head of the population	Vulnerability – Adaptive Capacity	V33
Fixed broadband coverage	Vulnerability – Adaptive Capacity	V34
Next Generation Access (NGA) – broadband	Vulnerability – Adaptive Capacity	V35
Urban area classified as green space	Vulnerability – Adaptive Capacity	V36
Urban land cover	Vulnerability – Adaptive Capacity	V37
Change in urban green space	Vulnerability – Adaptive Capacity	V38
Change in urban land cover	Vulnerability – Adaptive Capacity	V39
Priority allocation funding	Vulnerability – Adaptive Capacity	V40
Employment-population balance	Vulnerability – Adaptive Capacity	V41
Patent applications to the EPO	Vulnerability – Adaptive Capacity	V42
GVA per head of population	Vulnerability – Adaptive Capacity	V43

(*continued on next page*)

Table 1 (*continued*)

Indicator Name	IPCC AR5 Risk Domain	Radial Chart Ref.
Population in urban areas	Vulnerability – Sensitivity	V44
At Risk of Poverty	Vulnerability – Sensitivity	V45
Projected population change 0–14 (2017–2050)	Vulnerability – Sensitivity	V46
Projected population change 70+ (2017–2050)	Vulnerability – Sensitivity	V47
Migratory population change	Vulnerability – Sensitivity	V48
Projected change in population density	Vulnerability – Sensitivity	V49

advantage of this process is that the interpolation prediction takes account of values of surrounding polygons through the creation of the density surface (Krivoruchko et al., 2011).

Prior to any interpolation being undertaken, candidate variables were assessed for spatial autocorrelation. Global Morans *I* was calculated for each of the six variables were missing data was identified (Table 1: V42, V43, V46, V47, V48 and V49). Global Morans *I* statistics were calculated using edge and corner contiguity for each variable with a sensitivity analysis carried out using an inverse distance measure[4] based on the default threshold determined within ArcGIS. The contiguity-based Morans *I* statistic for V42 (GMI = 0.35, $p <.000$), V43 (GMI = 0.71, $p <.000$), V46 (GMI = 0.72, $p <.000$), V47 (GMI = 0.052, $p <.000$), V48 (GMI = 0.61, $p <.000$) and V49 (GMI = 0.72, $p <.000$) revealed that all six variables exhibited tendencies towards spatial clustering. This was also confirmed by the inverse distance measure for all six candidate variables, which supported the decision to adopt an interpolation-based approach as the means for inputting missing data.

The interpolation of variables is dependent on the accurate specification of predictive models. In ArcGIS, spatial interpolation takes place through the 'variography workflow' where the objective is to iteratively amend the parameters of the geostatistical model so that empirical covariances are estimated to fall within a series of confidence intervals that are set at points along a covariance curve. Under our approach, when the model is accurately specified, 90% of the covariances will coincide with the confidence intervals. Areal interpolation was carried out on the six candidate indicators. Various interpolation models were piloted with the k-bessel model being adopted following extensive testing (see Logan et al., 2014). The k-bessel model is one of the most functional in the ArcGIS Toolkit at fitting covariances, but this functionality is traded-off with significantly higher computational demands when compared to other lower-functional models available in the ESRI geostatistical toolkit.[5]

Finally, the transformed, standardised and where necessary the interpolated indicators were subjected to Pearson's Correlation. This test was performed on indicators within the same domain to identify indicators that were excessively correlated (+/-0.8 or greater) (Mooi and Sarstedt, 2011). This adds a necessary step in reducing data redundancy in the final typology. Redundancy in this context relates to the way in which the process or characteristics of one indicator is explained by the composition and structure of another indicator (e.g., see discussion of the control period, RCP 4.5 and 8.5 in Stage 1 above). Therefore, removing redundant indicators will not disadvantage the ECRT because the characteristics, processes or composition captured by the redundant indicator will be reflected in one of the retained indicators.

[4] Inverse distance was also used as a sensitivity measure to compensate for any incidence of NUTS3 regions not exhibiting edge and/or corner contiguity (i.e. where they were isolated from other NUTS3 regions).

[5] What is areal interpolation (ESRI) guidance?

Where indicators were excessively correlated, redundant indicators were removed from further analysis and the retained variables reconceptualised to reflect the revised scope of the indicator. Of the 81 indicators that were originally transformed and standardised, 49 candidate indicators were retained for inclusion in the final stage cluster analysis (for details see supplementary information – Appendix B).

2.3. Stage 3: Clustering and final typology development

Having cleaned and processed the data and identified a final suite of indicators, the next step was to identify groupings of NUTS3 regions based on their climate risk characteristics. *K*-means was adopted as the method of clustering for developing the ECRT. *K*-means is an unsupervised machine-learning technique that seeks to 'minimise within group variations' and to 'maximise between group variations'. The aim of the clustering exercise was to identify homogenous groups of NUTS3 regions that share similar climate risk characteristics. *K*-means clustering partitions objects into *k centroids* that are fixed a priori (MacQueen, 1967) where objects (i.e. NUTS3 units) are iteratively reassigned to clusters in an attempt to derive a series of centroids that minimise variation:

$$V = \sum_{x=1}^{k} \sum_{y=1}^{n} \left(z_x - \mu_y\right)^2$$

where n is the number of clusters and μ_y is the mean centroid of all the points z_x in cluster y (Longley and Adnan, 2016: 381).

No attempt was made to weight or give priority to certain variables over others prior to clustering. This decision was taken following consultation with project partners and stakeholders, which revealed highly polarised and often contradictory priorities among consultees depending on their knowledge, experiences, and their awareness of local circumstances. Here project partners and stakeholders argued for the equal weighting of indicators as the preferred option to maintain statistical robustness and limit the potential for the ECRT becoming a 'black box'.

In consultation with project partners and stakeholders, the decision was also taken to develop a typology that would consist of two 'tiers' – an upper-tier of 'classes' and a lower-tier of 'sub-classes'. Classes were conceived as a way of providing breadth of coverage while the sub-classes were defined to provide further depth to each of the individual classes (see Gale et al., 2016; Hincks et al., 2018 for similar structures). In this paper, we only report the development and analysis of the *class* structure.

Using IBM SPSS v.22 and bespoke syntax, the 49 candidate indicators selected for inclusion in the clustering exercise were tested through a series of pilot runs. One of the limitations of *k*-means clustering is that case order can affect the outcome of the cluster solution. In an effort to minimise these effects, cluster solutions were rerun using randomly ordered cases (NUTS3 units). This exercise was undertaken 5000 times for the class layer and 1000 times each for the 'sub-class' layers. The cluster method was set to 'iterate and classify' with stability being reached once the iteration of centroids between clusters had ceased. The initial focus of the analysis was on deriving a classification deriving n clusters that would constitute the upper-tier of classes that was constrained by an upper-limit of a maximum of 10 clusters. This upper-tier layer was then further partitioned into m_y clusters, which formed the lower-tier 'sub-class' layer (Gale et al., 2016). This sub-class layer was constrained to an upper-limit of a maximum of five clusters.

Another limitation of *k*-means clustering is that there are no set criteria for defining an optimum cluster solution. However, to inform decisions as to which solution is optimal, cluster distances were evaluated using diagnostic statistics. Post-hoc tests were calculated to determine whether the distances between cluster centroids for each solution were statistically significant and warranting their retention as separate clusters (see below). The different configurations of the indicator loadings in each class and sub-class definition were visualised as radial graphs that were then used to help profile the climate change risk captured by different classes and sub-classes (see below).

2.4. A new climate risk typology for European cities and regions

The first research question posed at the outset of the paper focused on identifying the characteristics of climate change risk in Europe's cities and regions. As set out above, the ECRT consists of two 'tiers' – classes and sub-classes. The class solution was optimised at an eight-fold structure (Fig. 2).

Each class represents a distinct group of cities and regions that share *similar* climate risk characteristics based on the indicators (hazard, exposure sensitivity and adaptive capacity) developed to underpin the ECRT. The second-tier, *sub-class,* structure (not considered here) consists of 31 groups developed through the segmentation of the eight classes to provide a further layer of disaggregation of understanding of climate change risk across European cities and regions.

The optimum solutions were identified based on those runs that minimised the 'within cluster sum of squares' (WCSS) statistic calculated as part of the cluster diagnostics. The WCSS measures how close objects within each cluster solution are to the centroid, indicating cluster homogeneity (Gale et al., 2016: 10). It is not possible to summarise the diagnostic results for all cluster runs undertaken, given that solutions were generated for 3–10 clusters 5000 times for the class layer. However, details of the top five best performing *class* solutions are summarised in Table 2.

Once the optimum number of clusters had been determined, a radial graph for each cluster was created (Fig. 3). Here standardised z-scores were plotted in relation to the grand mean score for all NUTS3 units in the analysis. This same approach was also applied in the development of the lower-tier sub-class solution (not shown).

The next step involved the profiling of each cluster based on their underlying characteristics. In developing the ECRT, indicators were assessed based on conceptual relevance and technical robustness. At times, this necessitated a trade-off in that some indicators that were conceptually robust may have only been collected for a single snapshot year and of these indicators, some were collected for different based years (i.e., 2017 and 2016). Minimising variation in the snapshot years is preferable but data availability and coverage means this is often difficult, especially when working at a continental or global scale (de Sherbinin, 2014). Other retained indicators were future orientated, based on projections of trends from a baseline year into the future while other indicators measured change over time, typically for a period over the recent past. Notwithstanding the limitations associated with data gaps, lags, and uncertainties in measuring climate change risk – a dynamic, multidimensional, and complex phenomenon – the *k*-means clustering technique can accommodate such variation in the indicator structures, especially where indicators are normalised and/or standardised in a consistent way.

However, the risk in adopting a combination of snapshot, change and projection indicators lies in the interpretation of the cluster outputs where the misreading of indicators can lead to erroneous attributions or qualities (ESPON Climate, 2022). To develop coherent cluster descriptions that were sensitive to differences in indicators and their measurement frameworks (i.e., snapshot, change or projection), the project team used the conceptual and metadata descriptions of the retained indicators developed in Stage 2 and aligned these to the radial graphs that were generated from the optimum clustering solution. Profiles of individual clusters were developed, and descriptions created for each of the groups in the climate risk classes and sub-classes designed to signpost the dominant characteristics underpinning each climate risk cluster (Fig. 3). This was undertaken iteratively with project partners and stakeholders as part of a collaborative exercise in profiling the clusters (Kingston et al., 2000).

The pen portraits of the eight classes, detailing the dominant variables in each cluster, are summarised below:

Class 1: The majority of the cities and regions in this class are concentrated in Eastern Europe and Central France. They face a wide range of climate change hazards relative to other NUTS3 areas, including fluvial flooding, rising temperatures and heat waves and wildfires. These areas show relatively high exposure of people, settlements and critical infrastructure to fluvial flooding from rivers, but less so to landslide hazards. They have relatively low provision of critical infrastructure and broadband/bandwidth capacity compared to other parts of Europe. This is related to their *peri*-urban and rural locations, which also reflects in their relatively low population densities and proportions of built-up area. In a European context, they have lower levels of GVA and employment opportunities, and as a result are in receipt of high levels of European funding via priority allocation schemes. This economic situation can also help to explain the projections for low levels of migration and numbers of young people in the population in the future. Due to the range of hazards faced, the notable exposure to fluvial flooding and relatively high levels of vulnerability, climate change risk is an important issue.

Class 2: This class encompasses a relatively small number of cities and regions sited in low lying and estuarine locations, particularly in the Netherlands and Denmark. Other regions sharing these characteristics, for example in North Eastern Italy and Northern Germany, also fall within this class. The key hazards they face are fluvial flooding and coastal hazards, that is well above the European average. Exposure of people, settlements and critical infrastructure to these hazards is also comparatively high. There are in relative terms lower proportions of the population at risk of poverty, and migration levels are projected to increase. GVA, employment prospects and patent application indicators are above the average for Europe's cities and regions. These locations also have relatively high critical infrastructure provision and access to broadband and high bandwidths. This suggests that capacity to adapt to hazards is relatively high and sensitivity relatively low. However, the potential severity of the hazards faced by these areas, and the high level of exposure to fluvial flooding and coastal hazards, marks climate change as a major risk factor into the future.

Class 3: This class is principally Mediterranean in distribution. Its cities and regions cover the majority of Portugal and Spain, France's Mediterranean coast, Italy, Croatia and Greece. These areas are hot and dry, and are projected to become increasingly so over the coming decades with climate change. Landslides and coastal hazards are a feature, with people, settlements and infrastructure currently exposed to both hazards, particularly landslides. High soil moisture stress and projected water consumption pressure increase the threat of water shortages and drought. Critical infrastructure provision and broadband/bandwidth capacity is relatively low from a European perspective. Urban population density is above the average for Europe, although the coverage of built-up areas and green spaces in urban areas is relatively low. Socio-economic indicators highlight that these areas face challenges, with higher than average levels of poverty risk, and lower than average GVA, employment prospects and patent applications. These factors potentially combine to increase vulnerability to climate change hazards and increase overall levels of climate risk.

Class 4: This class covers the majority of the coastal zones of the UK, northern France and Denmark. Parts of the Belgium, Netherlands and northern Germany are also included. Coastal hazards are a particular feature of these cities and regions. Given the relatively high urban population densities and numbers of transport nodes in these areas, this translates into high levels of exposure of people, settlements and infrastructure to coastal hazards in comparison to other parts of Europe. Conversely, exposure to fluvial flooding and landslide hazards is relatively low from a European perspective. Socio-economic indicators do not suggest that these are amongst Europe's most affluent and dynamic locations, although they also highlight that they are not amongst the poorest. The number of young people is projected to increase as is migration, and there is relatively good access to broadband and high internet bandwidths. These factors can help to moderate levels of vulnerability to coastal hazards, although the high degree of exposure to

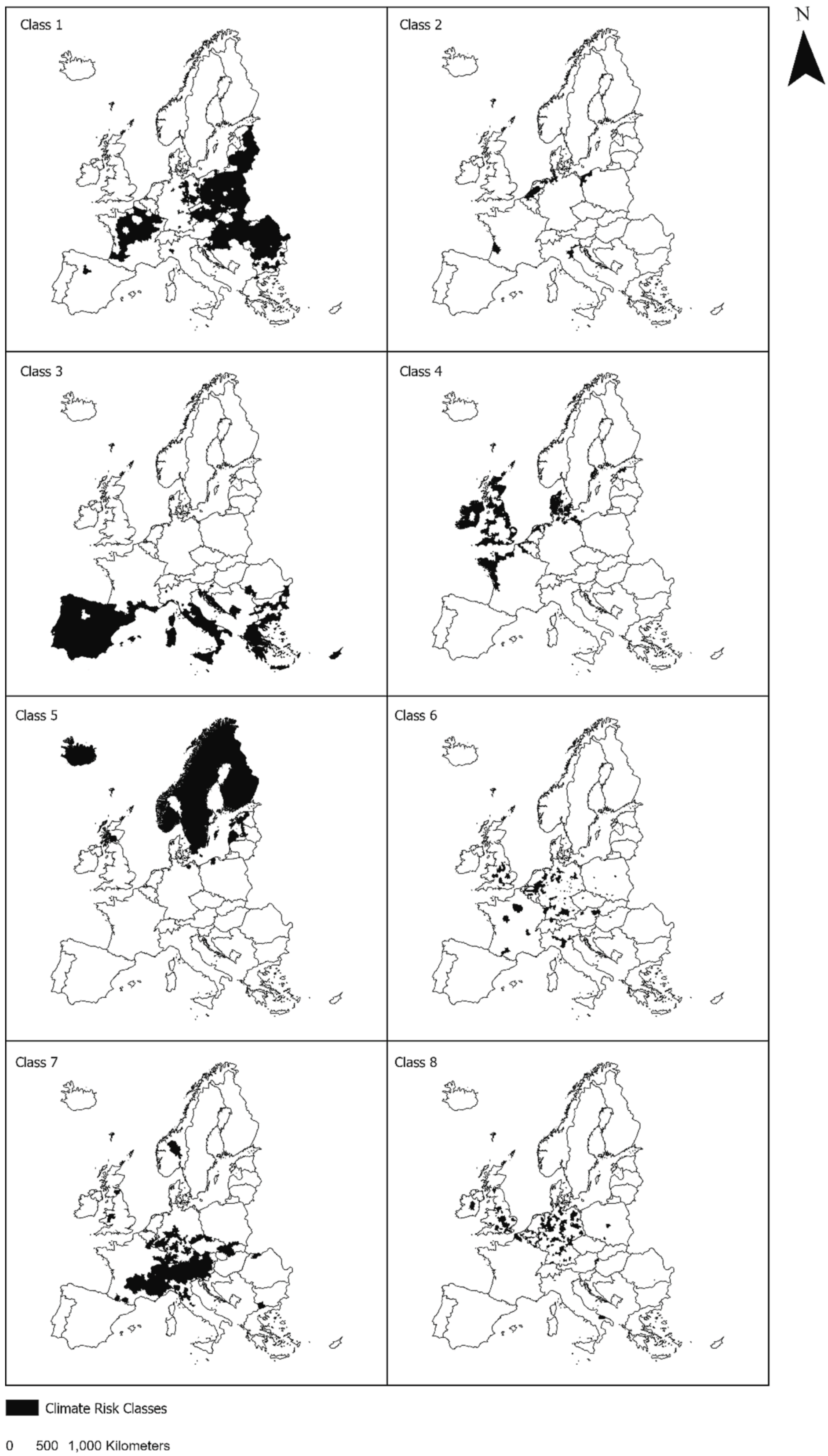

Fig. 2. Distribution of climate risk classes.

Table 2
Summary of diagnostic statistics for top five ranked class solutions.

Solution	Levene Statistic	WCSS	Optimised Cluster Solution
1	4.969, df1 7, df2 1371,. p <.000	53.3, df 1371, (p <.000)	8 clusters
2	4.118, df1 7, df2 1371,. p <.000	53.7, df 1371, (p <.000)	8 clusters
3	4.192, df1 7, df2 1371,. p <.000	53.7, df 1371, (p <.000)	6 clusters
4	4.087, df1 7, df2 1371,. p <.000	53.7, df 1371, (p <.000)	8 clusters
5	4.023, df1 7, df2 1371,. p <.000	53.7, df 1371, (p <.000)	6 clusters

this hazard places climate change as a key risk to economic development, health, and wellbeing.

Class 5: These cities and regions are located in Northern Europe. Aside from Denmark, much of Scandinavia falls within this class. Parts of Western Scotland, the Baltic States and Iceland (aside from Reykjavik) are also encompassed. These are cool and wet areas, although temperatures are nevertheless rising at a higher than average rate for Europe, with the number of ice days projected to fall significantly. They are also projected to experience a large increase in heavy and very heavy precipitation days compared to other European locations, which may increase the chance of surface water flooding in some areas. Coastal hazards are a threat, which results in high exposure of people, settlements and critical infrastructure to this hazard. These are often large areas with relatively low urban population densities and many smaller rural settlements. Urban areas have high levels of green space, and are not densely built up. Broadband and bandwidth capacity are relatively low, as is the density of transport networks with low numbers of road intersections and transport nodes. Due to low population densities, the number of critical infrastructure assets per 1000 people (e.g. airports, hospitals etc.) is high from a European perspective. Socio-economically, these affluent and dynamic places with projected increases in migration 594 and numbers of young people over the coming decades. This could increase capacity to adapt to the changing climate.

Class 6: In this class, cities and regions are predominantly located in Central and Western Europe. Fluvial flooding from rivers is the key climate hazard facing these areas. There is also the potential for greater surface water flooding arising from projected increase in heavy rainfall events over the coming decades. Exposure of people, settlements and critical infrastructure to fluvial flooding is currently relatively high in a European context while exposure to landslides is relatively low. These are comparatively affluent and innovative areas compared to the European average and are projected to experience increase in migration and numbers of young people. They also have well developed road networks and high broadband access and bandwidth capacity. For reasons such as these, they have relatively low sensitivity to climate change hazards and high adaptive capacity, and their vulnerability to climate change is therefore relatively low. However, given that exposure to fluvial flooding is high, climate change and extreme weather is a risk.

Class 7: This class covers the Alps, upland areas of Germany, parts of the Carpathian Mountains, and France's Massif Central and Eastern mountain ranges. Aside from several areas in Italy, all cities and regions are inland. The topography and high rainfall levels contribute to landslides standing out as a key hazard. Climate change is projected to increase the frequency and intensity of heavy and very heavy rainfall days, which could result in an even greater landslide hazard. It is therefore understandable that the exposure of people, settlements and critical infrastructure to landslides is high from a European perspective. Here, high transport infrastructure densities (road intersections, transport nodes) stand out as a particular issue, although population densities are relatively low. Exposure to fluvial flooding is also relatively high. Projections for climate change induced intensification of extreme rainfall may drive exposure levels higher still. These areas are relatively affluent and innovative compared to others in Europe, and are projected to experience increasing migration in the future. Climate change poses a range of risks to these regions over the coming decades, although their relatively high levels of adaptive capacity may help to moderate risk.

Class 8: England, Belgium and Germany dominate this class, although there are outliers in France, Poland and Austria. These are predominantly inland cities and regions. Projections highlight that they will experience an increasing number of consecutive wet days and days with heavy and very heavy rainfall. Aside from this, their hazard profile is relatively benign. As a result, exposure to hazards including fluvial flooding, landslides and coastal hazards is low in relation to other parts of Europe. These are generally urbanised areas with above average population densities, urban built environment coverage and numbers of road intersections and transport nodes (reflecting dense transport networks). GVA, employment prospects and patent applications indicators are at a level above the European average, suggesting higher levels of adaptive capacity to climate change hazards. This can help to moderate risks associated with increasing rainfall (and potential fluvial and surface water flood risk) that these areas may face in the future.

2.5. Analysing climate risk for European cities and regions

Having outlined above the broad structure of the new climate risk typology, this section offers an analysis of the patterns and trends in climate risk revealed through the ECRT.

2.5.1. Distribution of climate risk classes

Here we draw on a selection of trends in the eight-fold class configuration to provide an analysis of the distribution of climate change risk across Europe. Focusing initially on the distribution of climate risk for each of the classes by NUTS3 regions (Table 3), it is notable that four classes – 1 3, 7 and 8 – have distributions of NUTS3 regions that exceed the median distribution of 14.7 %. Class 7 was the top-ranked cluster on this measure accounting for over 18 % of NUTS3 regions encompassing areas including the Alps, France's Massif Central and Germany's uplands. Next, classes 1 and 3 account for 18 and 16 % of NUTS3 regions respectively. Class 1 is concentrated principally in Eastern Europe and interior regions of central France where class 3 is widely distributed through the Mediterranean. Class 8 accounts for 15 % of NUTS 3 regions and is distributed through central and northern Europe – notably Germany, Belgium, and the UK.

In contrast, classes 2 and 5 account for the smallest proportions of NUTS3 regions by a notable extent at 3.5 % and 4.9 % respectively. Class 2 is concentrated around the Netherlands, Germany's North Sea and Baltic coasts and Italy's northern Adriatic coastline while class 5 is largely concentrated through Scandinavia. Finally, class 4 accounts for nearly 10 % of NUTS3 regions and is a feature of northwestern coastal regions where class 6, at just over 14 % of NUTS3 regions, is distributed throughout central and western Europe.

Fig. 4 summarises the proportion of NUTS3 regions per country that fall into each of the climate change risk classes. Class 1 occurs to a greater or lesser extent in over half (52 %) of all countries (n = 17/33) covered by the ECRT while classes 3, 6 and 7 occur in 39–49 % of countries. Classes 5 and 8 are found in approximately one-third (31 and 36 % respectively) of all countries while classes 2 and 4 occur in approximately one-quarter (24 and 27 % respectively).

Fig. 5 summarises the climate change risk occurring within each country split between the different classes. It is notable that most countries are characterised by a single risk class or where the distribution is dominated by a single class. Yet within this principal pattern, there is also evidence of extensive variation in climate change risk within and between countries across Europe.

Analysis of these patterns reveals areas of homogeneity in the climate risk profile of countries where in 61 % of the countries covered by the ECRT, all NUTS3 regions fall into one typology type or one type that is

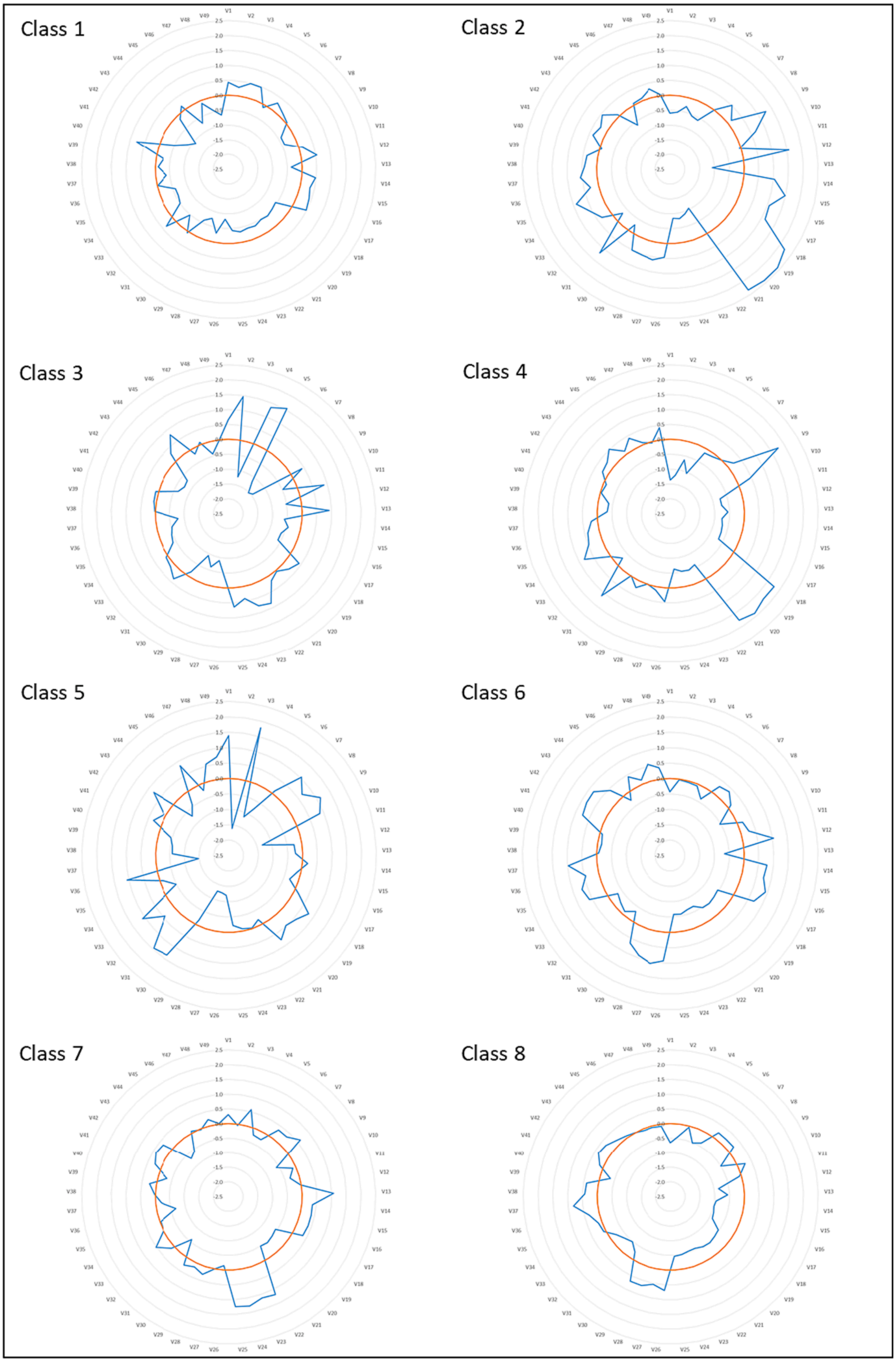

Fig. 3. Class radial graphs *NB – Red line is the class mean.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Summary of distribution of climate risk for each of the classes by NUTS3 regions.

Class	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Median
% NUTS3	18.0	3.5	16.2	9.6	4.9	14.4	18.4	15.0	14.7

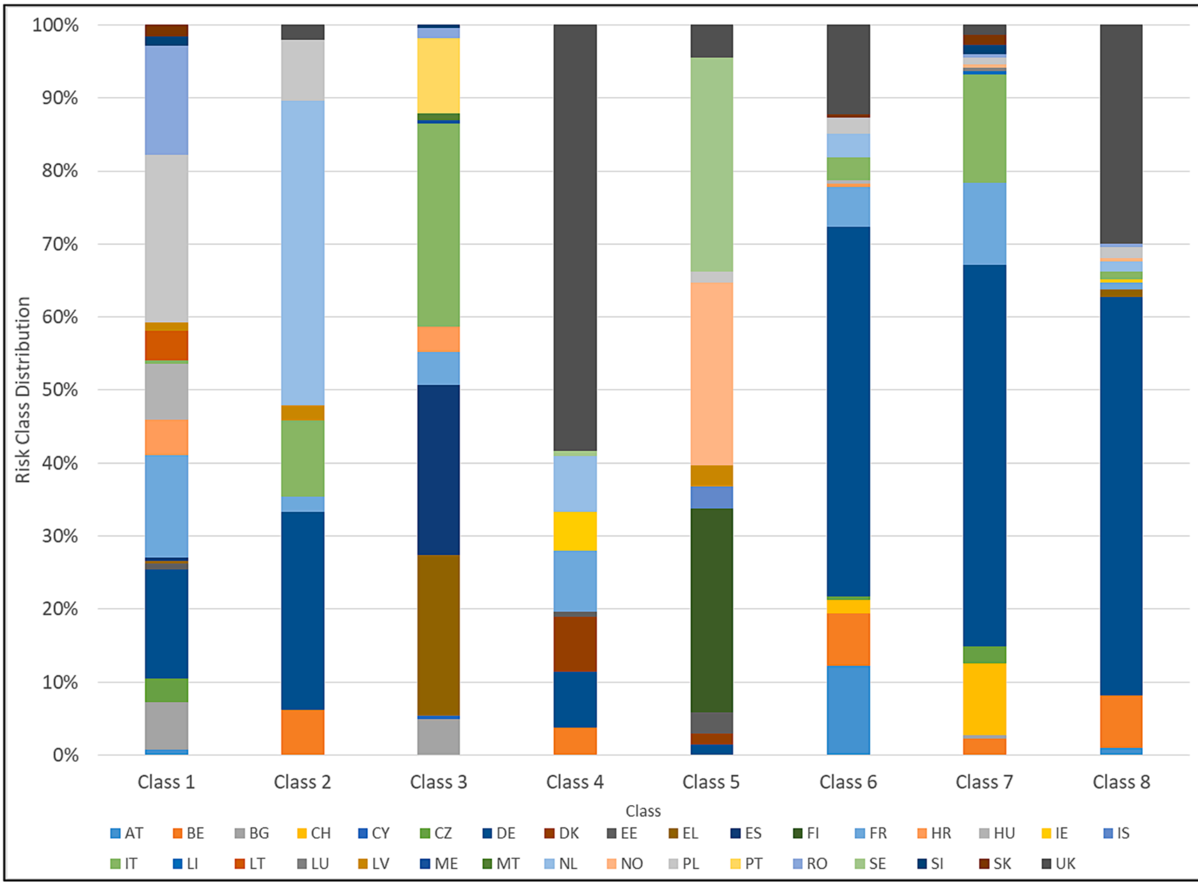

Fig. 4. NUTS3 regions per country that fall into each of the climate change risk classes (%).

dominant, accounting for over 75 % of NUTS3 regions. At the same time, six countries have evidently heterogeneous risk profiles where four or more types are present and no single type accounts for more than 80 % of total NUTS3 regions in the country. Where homogeneity is most acute is in countries where the number of NUTS3 regions is relatively limited (e.g. Cyprus, Iceland) whilst heterogeneous profiles are most pronounced in counties with more granulised NUTS3 geographies (e.g. Germany).

By its design then, the clustering procedure will have conditioned the underlying structure of the climate change risk classification through the methodological decisions taken, including the adoption of NUTS3 regions and the choice of candidate variables to include. Nevertheless, the ECRT underlines the extent to which climate change hazards and the drivers influencing exposure and vulnerability vary between cities and regions, reinforcing the IPCC message that adapting and building resilience to climate change risk is not a 'one-size-fits-all' exercise (Chair of the IPCC, 2017).

2.5.2. *The urban–rural question*

At this point, our analysis turns to the next research question, which focuses on determining whether there are differences between 'urbanised' NUTS3 regions and those that are either urban hinterlands or rural regions. In part, this focus was a rejoinder to the observation that "responses of human societies [to climate change risk] vary with the types of settlements, leading to the need to differentiate between urban and rural areas, their specific climatic conditions, associated livelihoods and levels of poverty" (Chair of the IPCC, 2017: 24).

In considering this issue, the following approach was undertaken. First, Eurostat's urban–rural typology[6] – which segments NUTS3 regions into *predominantly urban, intermediate*, and *predominantly rural* regions based on land-use and population density measured at 1 km^2 resolution – was adopted as a proxy of urban, rural and intermediate regions. Second, chi-square (X^2) was undertaken to test whether there was a significant association between climate change risk based on classes (n = 8) and settlement type (n = 3) (Table 4).

The X^2 reveals that there was a significant association between settlement type and climate risk (X^2 = 307.558, p <.001) with Cramer's V indicative of a moderate strength of association (φ=0.472, p <.001). The challenge in interpreting this relationship, however, is that the associated X^2 statistic is derived based on 24 separate analyses (8x3 contingency table) for which there is no indication in the X^2 measure as to which combinations of settlement types and climate change risk classes are statistically significant. To shed light on this, an adjusted residual (z-score) was calculated for each analysis and while these can

[6] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Territorial_typologies_manual_-_urban-rural_typology.

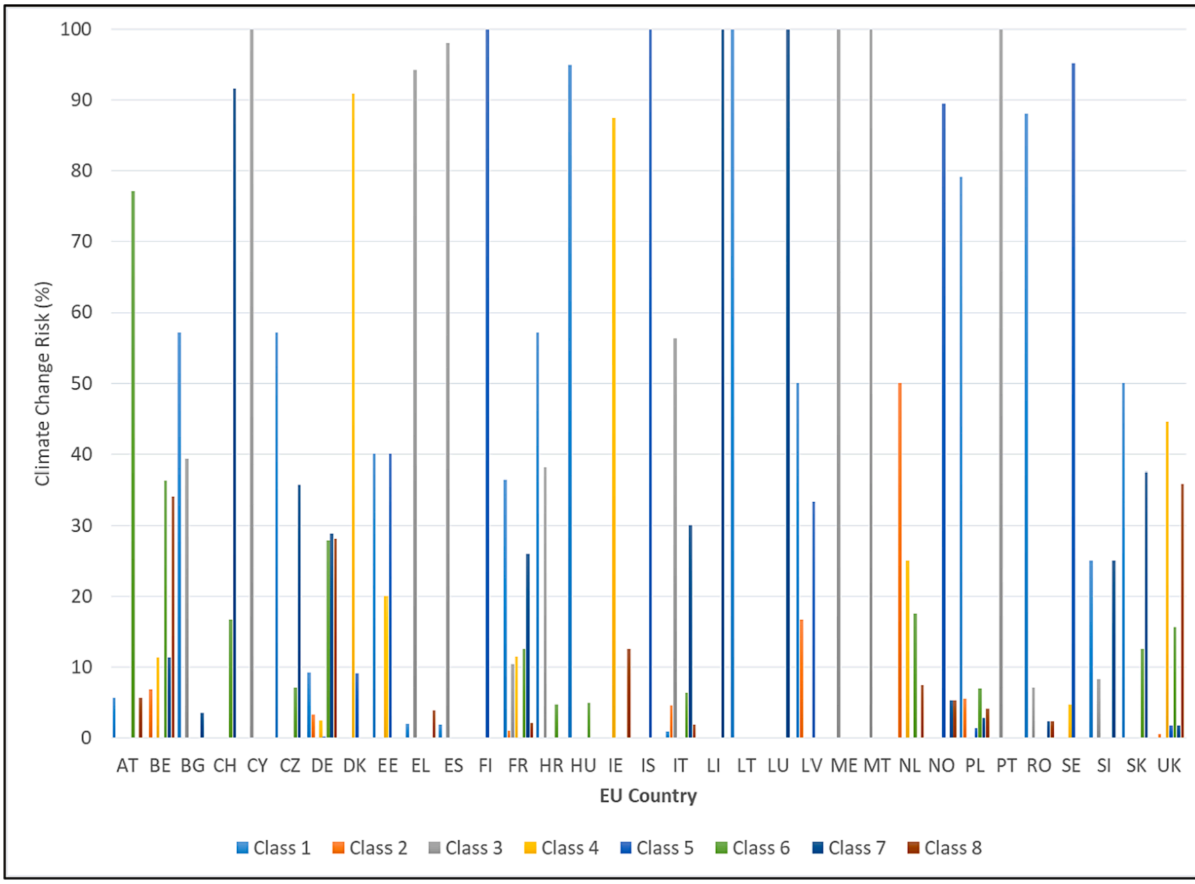

Fig. 5. Climate change risk occurring in each country by class (%).

be compared to a critical value of 95 % ($z = \pm 1.96$), simply considering the adjusted residuals would run the risk of a Type I error.[7] Instead, the adjusted residuals were used to calculate a right-tailed *probability* of the chi-squared distribution with a Bonferroni correction used where $\alpha = 0.05$ was adjusted so $\alpha = 0.05/24 = 0.00208$.

What is revealed through the Bonferroni corrected probability statistic is that the relationship between intermediate areas and climate risk classes were not significant for any of the interactions except for classes 4 and 7. However, the relationship between predominantly urban NUTS3 regions and climate risk classes were statistically significant for all interactions. Likewise, the relationship between predominantly rural and climate risk classes were statistically significant for all interactions except for class 3.

Several insights are revealed here. The first is the extent of variation in climate change risk facing urban areas of Europe that brings into sharp focus the challenges created by the current unevenness in the way urban adaptation is experienced, resourced, and governed across Europe (Aguiar et al., 2018; Landauer et al., 2019; Olazabal and Ruiz De Gopegui, 2021). The finding also supports the IPCC focus on accounting for urban–rural differences in developing adaptation and mitigation strategies, where climate risk profiles intersect with settlement types in variably complex ways (Chair of the IPCC, 2017).

Finally, based on the ECRT, there is a risk that intermediate areas – lying between distinctly urban and rural contexts, at least in EU statistical terms – fall between climate change risk agendas or priorities. Such 'peri-urban' areas are typically characterised by fluid and complex socio-spatial structures and "fragmented and overlapping institutional landscapes" that typically mean "…that coherent spatial strategy is generally lacking" in such areas (Rauws and de Roo, 2011: 270). Notwithstanding the fact that the ECRT is likely to have privileged the 'extremes' of the settlement hierarchy due to the indicators included, intermediate areas would benefit from further detailed analysis using the sub-class structure to reveal a more granular profile of climate change risk facing *peri*-urban areas than is possible at the class level.

2.5.3. *The spatial clustering of climate change risk*

The final component of our analysis considers the extent to which climate change risk classes exhibit patterns of spatial clustering, where evidence of transboundary climate risks can inform decisions about the development of cross-border adaptation responses (Chair of the IPCC, 2017: 30). In doing so, we employed a geospatial technique to measure the degree to which NUTS3 regions cluster in space as a product of their underlying risk class. Here spatial clustering was measured using *local join count statistics*, a special case of 'local indicators of spatial association' (LISA) calculated using the GeoDa software (Anselin, 2020). LISA are a suite of statistics used to decompose global spatial autocorrelation to measure the degree to which, in this case, a NUTS3 region is similar in terms of its climate change risk profile to NUTS3 regions surrounding it (see Anselin et al., 2005). As the climate change risk classes are categorical inputs, so *univariate local join count* statistics were calculated for each climate change risk class by splitting the classes into discrete variables and then re-coding these as binary indicators (1 = presence of climate risk class; 0 = absence of climate risk class). The *local join count statistic* is expressed can be expressed as:

$$BB_i = x_i \sum_j w_{ij} x_j.$$

where w_{ij} are a spatial weights matrix that identifies whether i and j are adjoining locations (Anselin and Li, 2019: 191).

[7] Type I errors occur in rejecting a null hypothesis when it is true.

Table 4
Chi-Square - relationship between climate change risk class and settlement type.

Class		Predominantly Urban	Intermediate	Predominantly Rural
1	Count	12	98	138
	Expected	68.7	100.7	78.6
	Count	−8.9	−0.4	9.0
	Adj. Residual	0.00000*	0.69874	0.00000*
	Probability[a]			
2	Count	23	21	4
	Expected	13.3	19.5	15.2
	Count	3.2	0.5	−3.5
	Adj. Residual	0.00144*	0.65198	0.00040*
	Probability[a]			
3	Count	43	103	78
	Expected	62.1	91.0	71.0
	Count	−3.1	1.8	1.1
	Adj. Residual	0.00188*	0.07358	0.27099
	Probability[a]			
4	Count	62	42	28
	Expected	36.6	53.6	41.8
	Count	5.2	−2.2	−2.7
	Adj. Residual	0.00000*	0.03056*	0.00651*
	Probability[a]			
5	Count	9	28	31
	Expected	18.8	27.6	21.5
	Count	−2.7	0.1	2.5
	Adj. Residual	0.00626*	0.92217	0.01152*
	Probability[a]			
6	Count	111	72	15
	Expected	54.8	80.4	62.7
	Count	9.6	−1.3	−7.9
	Adj. Residual	0.00000*	0.18869	0.00000*
	Probability[a]			
7	Count	31	118	105
	Expected	70.4	103.1	80.5
	Count	−6.1	2.1	3.7
	Adj. Residual	0.00000*	0.03564*	0.00025*
	Probability[a]			
8	Count	91	78	38
	Expected	57.3	84.1	65.6
	Count	5.7	−0.9	−4.5
	Adj. Residual	0.00000*	0.35213	0.00001*
	Probability[a]			

$X^2 = 307.558$, df14,.p <.000 (0 cells have expected count less than 5)
φ=0.472, p <.001 (moderate association)
Probability Value (* p < 0.05 using Bonferroni correction where α = 0.00208)

Here a 'count' is taken where x_j and $x_i = 1$. As a result, the *univariate local join count* statistic is appropriate if the goal is to determine whether locations (e.g., NUTS3 units) with an observation (e.g., $x_j = 1$) are surrounded by more locations with an observation (e.g. $x_i = 1$) than would occur under randomness (Anselin and Li, 2019: 193).

In our case, for each re-coded climate risk class, this involves identifying NUTS3 regions where climate risk classes (coded as 1) are surrounded by more NUTS3 regions where a climate risk class is also present (i.e., coded as 1) than would occur under randomness. To determine co-occurrence, it is first necessary to define a spatial weights matrix to measure the spatial dependence of each NUTS3 region compared to neighbouring regions. GeoDa offers two main approaches for calculating weight matrices: *distance* and *contiguity* methods. Distance weights are calculated between target features to create distance-band weights. These reflect the connectivity of, in our case, NUTS3 regions based on critical distance thresholds that are understood to determine the influence of processes of interest (e.g., climate risk). Contiguity or adjacency-based weights reflect a relationship where spatial units share a common boundary and proximity structure (see below).

In specifying spatial weights however, there is no perfect solution. After extensive testing, using distance weights for polygons (NUTS3 regions) of significantly varying sizes and determining appropriate critical distance thresholds to measure the spatial dependence of climate change risk on NUTS3 regions presented notable conceptual as well as analytical challenges. Instead, it was decided to adopt contiguity weights to measure spatial dependence of climate change risk across NUTS3 regions (Fig. 6). While this decision also presents certain limitations – notably in areas where NUTS3 regions have few neighbours (e.g. Iceland or Cyprus) – contiguity offered a way, in this case, of systematically testing how the clustering of climate risk changes as contiguity changes. Rook and Queen-based contiguity measures were tested (Fig. 6 A and B) and queen-order contiguity was adopted with orders of proximity measured at first-, second-, and third-order extents.[8]

Univariate local join count statistics were calculated for each climate change risk class where the significance of spatial clustering was measured at 90 %, 95 % and 99 % confidence intervals. The proportion of NUTS3 regions, defined as significantly spatially clustered, was calculated for each climate change risk class individually (Fig. 7).

What is clear is that for all classes, climate change risk exhibits evidence of spatial clustering, but the extent of the clustering varies between different classes as contiguity changes. Classes 1, 3, 5 and 7 exhibit the most consistent patterns of clustering as a proportion of all NUTS3 regions in each class respectively. Classes 6 and 8 exhibit the lowest degree of clustering, which is pronounced at first-, second and third-order contiguity when compared to other classes.

Fig. 8 summarises how the proportion of spatially clustered NUTS3 regions changes as contiguity changes. Here the proportion of spatially clustered NUTS3 regions increased between the first and second-order contiguity for classes 2, 3, 4, 6 and 8 but declined for classes 1, 5 and 7, indicating a higher propensity for dispersion in these risk classes between first and second-order contiguity. This propensity for dispersion was also evident when taken account of change in clustered NUTS3 regions between first and third-order contiguity for classes 1 and 5. Between second and third-order contiguity, the proportion of additional NUTS3 regions included in the clustering around the first-order contiguity increased for all classes except classes 5 and 8 – which remained stable – but the additionality was less pronounced than between first and second order contiguity.

The analysis demonstrates the value in revealing sub-national structures of climate change risk where accounting for underlying attributes (i.e., characteristics of hazard, exposure and vulnerability) *and* spatial context (i.e., clustering) exposes a complex landscape of risk across Europe that was previously unavailable. Within each risk class there are notable concentrations of clustering some of which are geographically extensive. These are illustrated through the areas of red in Fig. 9, which represent areas where the target NUTS3 unit is immediately adjacent to other NUTS3 units of the same risk class (Q1). Nevertheless, in all risk classes – albeit to varying degrees – the spatial clustering of risk is interrupted. This is represented in Fig. 9 by areas of underlying grey where the NUTS3 units do not belong to the risk class under consideration or where contiguity breaks down beyond first, second and third-order effects, the latter represented by areas of blue (Q2) and black (Q3) respectively.[9] The result is that certain risk classes exhibit greater spatial fragmentation (e.g., class 7) than others owing to their underlying structural characteristics while other risk classes exhibit greater spatial concentration (e.g. class 3).

This analysis of spatial clustering reinforces the need for transboundary adaptation responses to reflect both continuities and discontinuities in risk profiles that transcend administrative (e.g., local government or national) boundaries in complex, uneven and at times fragmented ways (also see Adger et al., 2018; Birkmann et al., 2021;

[8] The order of proximity was measured to six-degrees, but it was found that a maximum third-order proximity performed best before change in distribution of NUTS3 regions effectively stabilised.

[9] Where contiguity breaks down, the target NUTS3 unit is so isolated that there are more than three other NUTS3 units between it and a NUTS3 unit of the same risk class.

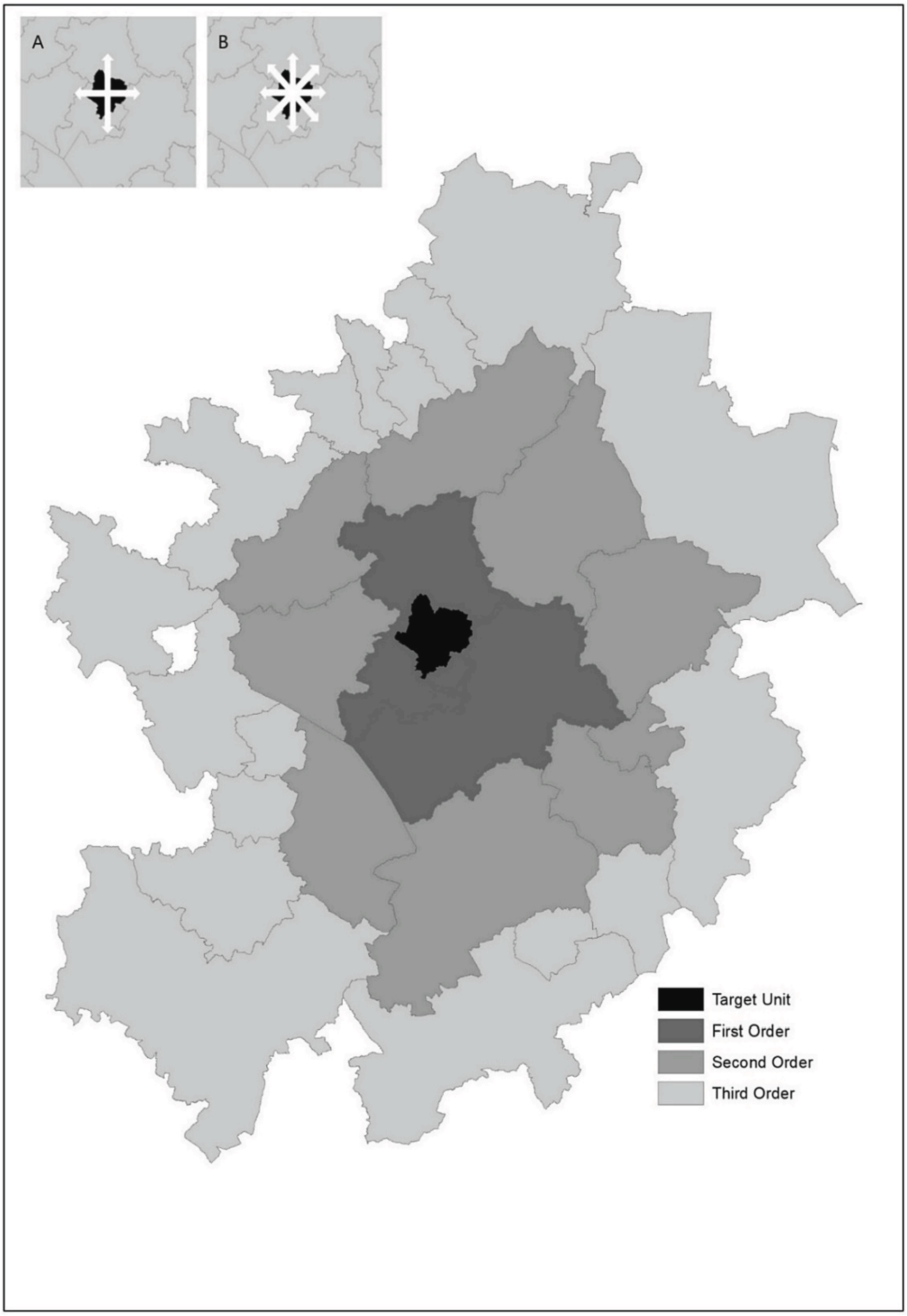

Fig. 6. Contiguity-based proximity of different orders *NB: A = Rook-contiguity (4-point direction); B = Queen-contiguity (8-point direction)*.

ESPON Climate, 2022) (Fig. 9).

3. Discussion and conclusion

This paper reports on a new and novel typology of climate risk developed for European cities and regions at NUTS3 level as part of a European funded Horizon 2020 RESIN project. The ECRT captures climate risk facing European cities and regions and their underlying physical infrastructures. The novel contribution of the ECRT lies in its integration of hazard, exposure and vulnerability domains into a *composite*, spatially-explicit classification that covers the whole of Europe. It does so at a regional scale across Europe in a way that seeks to contribute to 'hot spot' mapping of climate change risk through a data-driven framework (see de Sherbinin, 2014; de Sherbinin et al., 2019). In doing so, the ECRT responds to the IPCC's risk-based framework and its contention that scientific effort should be directed to a greater extent towards "…improving spatial resolution within regions and reducing uncertainties when filling knowledge and data gaps" (Chair of the IPCC, 2017: 7).

Against this backdrop, four research questions were posed at the outset of the paper. The first and second question focused on identifying the structure and characteristics of climate change risk facing Europe's cities and regions (see Dickson et al., 2012). While the design of the clustering procedure will have conditioned the underlying structure of

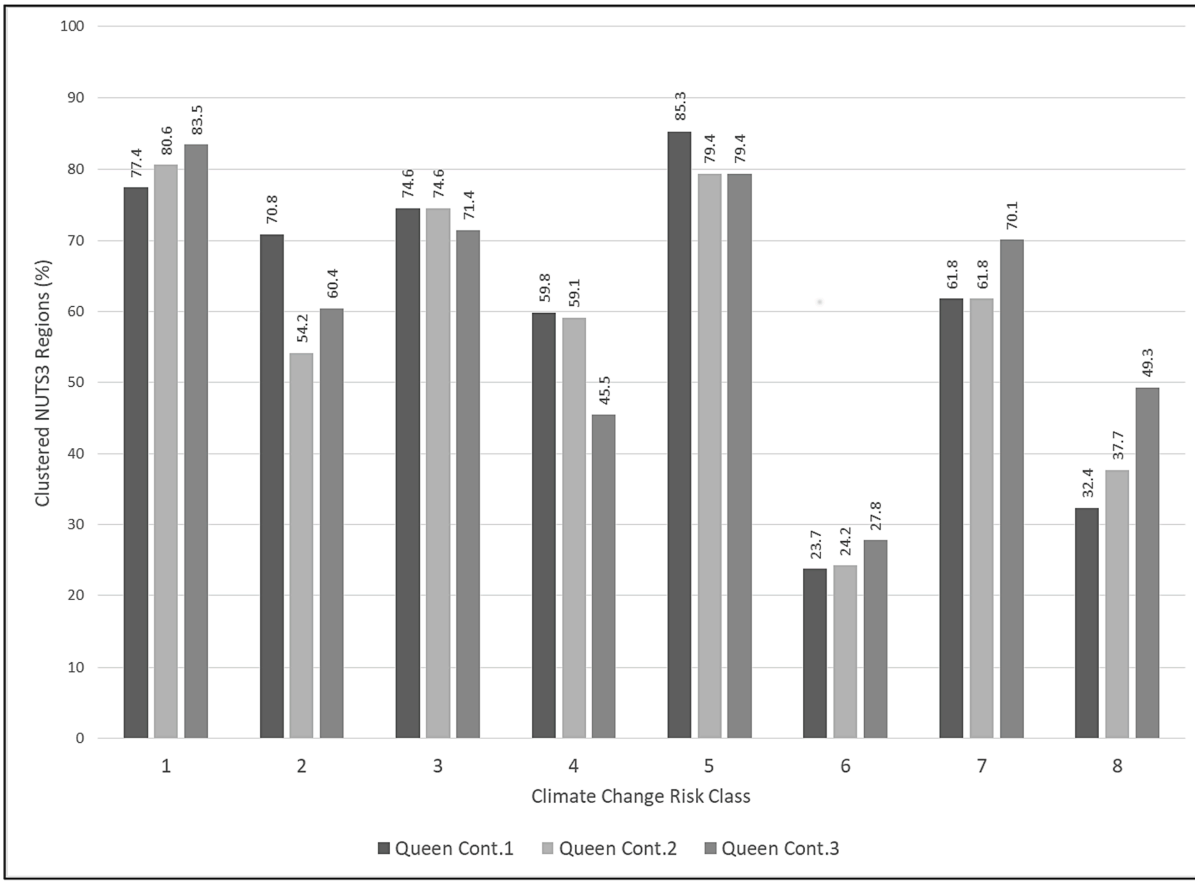

Fig. 7. Number of climate risk classes present within European countries *NB – Proportions are calculated as a total of NUTS3 regions in each climate risk class.*

the climate change risk classification, our approach identified an upper-tier solution of eight classes that were subsequently partitioned to derive a lower-tier classification of 31 sub-classes. The analysis in this paper focused, for brevity, on the class layer, revealing an uneven distribution of climate change risk classes across the 33 countries covered by the ECRT and reinforcing the IPCC message that adapting and building resilience to climate change risk is not a 'one-size-fits-all' exercise (Chair of the IPCC, 2017).

The third question asked whether there was a difference in the climate change risk across different settlement types in Europe (see Aguiar et al., 2018). At this point, the ECRT class layer was aligned to Eurostat's urban–rural typology, which segments NUTS3 regions into predominantly urban, intermediate, and predominantly rural regions based on population density and land-use measured at 1 km^2 resolution. The analysis revealed that the relationship between intermediate areas and climate risk classes were not significant for any of the interactions except for classes 4 and 7. However, the relationship between predominantly urban NUTS3 regions and climate risk classes were statistically significant for all interactions. Likewise, the relationship between predominantly rural and climate risk classes were statistically significant for all interactions except for class 3.

The implication of this analysis is important in highlighting the extent of variation in climate risk facing urban areas of Europe that brings into sharp focus the challenges created by the current unevenness in the way urban adaptation is experienced, resourced, and governed across Europe (Aguiar et al., 2018). The findings also support the IPCC focus on accounting for urban–rural differences in developing adaptation and mitigation strategies, where climate risk profiles intersect with settlement types in variably complex ways (Chair of the IPCC, 2017).

The ECRT was highlighted that intermediate, *peri*-urban areas would benefit from further detailed analysis using the sub-class structure to reveal a more granular profile of climate change risk than is possible at the class level. Peri-urban areas represent dynamic 'transitional zones' between the city and the hinterland "…where new spatial functions and land-use types arise through interaction between urban and rural elements" (Rauws and de Roo, 2011: 269). The findings here are apposite for Europe and beyond where in different places intensifying urbanisation is putting increasing pressure on *peri*-urban areas and threatening the multifunctional resources that are crucial in heat and hydrological regulation (e.g., vegetation and soils) (Gupta et al., 2017). At the same time, de-urbanisation and shrinkage in other contexts offers opportunities to expand green infrastructure and eco-system services in ways that are potentially transformative for climate change adaptation (Carter 2018, Meerow and Newell, 2017). Notwithstanding the fact that the ECRT is likely to have privileged urban–rural differentiation owing to the indicators that underpinned its development, the analysis highlights a risk in *peri*-urban areas falling between strategic climate change priorities by virtue of their 'transitional nature' (Gupta et al., 2017).

The fourth question explored the extent to which different types of climate change risk cluster spatially across Europe (see Metzger and Schröter, 2006). This involved the use of univariate local join count statistics (Anselin and Li, 2019) to measure the degree to which a NUTS3 region is similar in terms of its climate change risk class to NUTS3 regions surrounding it. Focusing variably on three orders of contiguity, local join count statistics were calculated for each climate change risk class where the significance of spatial clustering was measured at 90 %, 95 % and 99 % confidence intervals. The analysis demonstrated that for all classes, climate change risk exhibits evidence of spatial clustering but that the extent of clustering varies between different classes as contiguity changes. This finding has notable implications for transboundary responses to climate change risk where discontinuities in political buy-in, coopetition, resourcing and awareness of risk could serve to

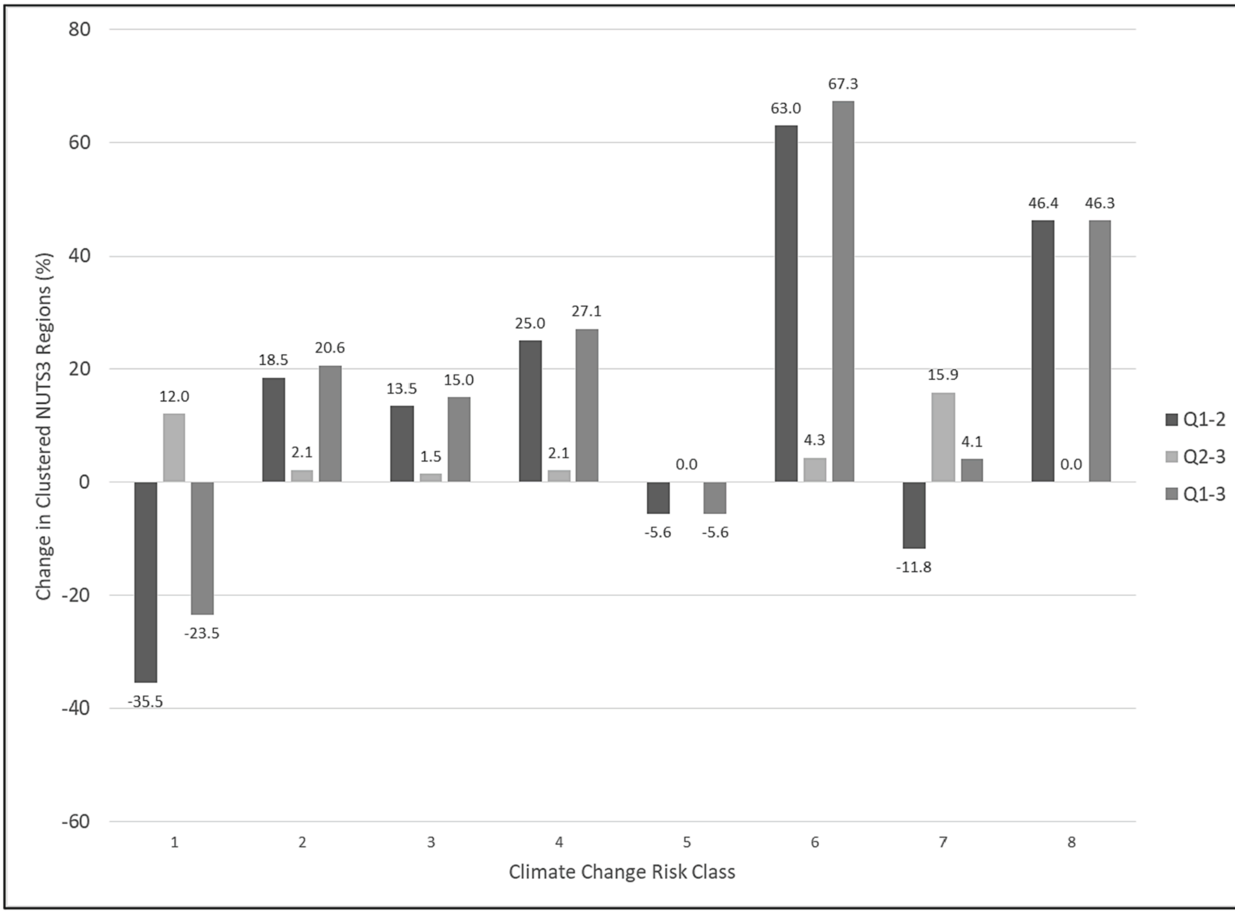

Fig. 8. Number of climate risk classes at NUTS3 Level.

undermine the coherence and adequacy of interventions at a time when greater cooperation and alignment is needed (Chair of the IPCC, 2017; Adger et al., 2018; Landauer et al., 2019; Birkmann et al., 2021).

Set against the insights on climate risk offered by the ECRT, there are limitations to recognise and avenues to consider for further analytical development in the future. First, the use of NUTS3 units was a compromise in ensuring European-wide consistency of the unit of analysis but the wide variation in the density and size of NUTS3 regions needs to be acknowledged. That Germany is comprised of 402 NUT3 units and Cyprus is a single region creates challenges in granulising the analysis and interpreting the trends reflected in the typology. Here we contend that the ECRT and its associated indicators are most valuable in supporting a strategic adaptation planning, acting to determine factors influencing climate risks at regional and national scales that need to be investigated in more detail as part of a wider analytical, evidencing or case-making agenda (see Füssel, 2007; anonymised for review).

Second, it is important to acknowledge the trade-offs underlying the development of the ECRT. Data coverage and quality is inconsistent across European countries, creating notable challenges in monitoring climate change risk (Connelly et al., 2015). This included having to adopt strategies for estimating missing data (e.g., interpolation), recognising the limitations in adopting datasets that were temporally inconsistent, and combining snapshot and projection indicators. It was also not possible to gather or develop indicators that covered all aspects of climate risk due to issues of data quality, access, and universal availability. Therefore, issues that are potentially important in determining climate risk, such as exposure of people and infrastructure to heat stress, are not covered in the ECRT indicator set. Likewise, indicators covering themes including governance approaches, social infrastructure and cultural assets and attitudes to climate change risk are largely absent. Similarly, we recognise that built environment assets will respond variably when exposed to climate hazards depending on key characteristics such as age and material use (Carter et al., 2015).

Our approach to data handling and processing ensured the approach taken was robust and consistent with data handling conventions adopted elsewhere (e.g. ESPON Climate, 2022) but nevertheless, it is important to recognise that these factors will have important implications for understanding climate change risk and related responses (Young and Essex, 2020) that mean that interpretations of the risk categories and profiles and their applications to climate change risk analysis needs to do undertaken sensitively in full recognition of the coverage of the indicators used (see de Sherbinin, 2014; ESPON Climate, 2022).

Third, typology development is both a science and an art (Gale et al., 2016). While decisions in developing the ECRT were taken to maximise the robustness of the outcome, the typology is essentially a product of the methodological choices made during its development (see Krivoruchko et al., 2011; Logan et al., 2014). This includes recognising limitations associated with using proxy measures for variables that are not directly measured or are difficult to capture, the use of data with inconsistent timeframes, missing data estimation, and variation in spatial resolution of indicators used in the ECRT (de Sherbinin, 2014). Herein lies a risk where users simply assume that a statistically derived typology is somehow 'objective' when in fact there is always subjectivity involved in typology development (Gale et al., 2016).

In future, there are possibilities to extend the analysis of the classification undertaken in this paper by incorporating the sub-class differentiation that would provide further granularity to the spatial interpretations of climate change risk documented here. This includes extending the climate risk and settlement type analysis that was undertaken alongside considering whether different sub-classes also

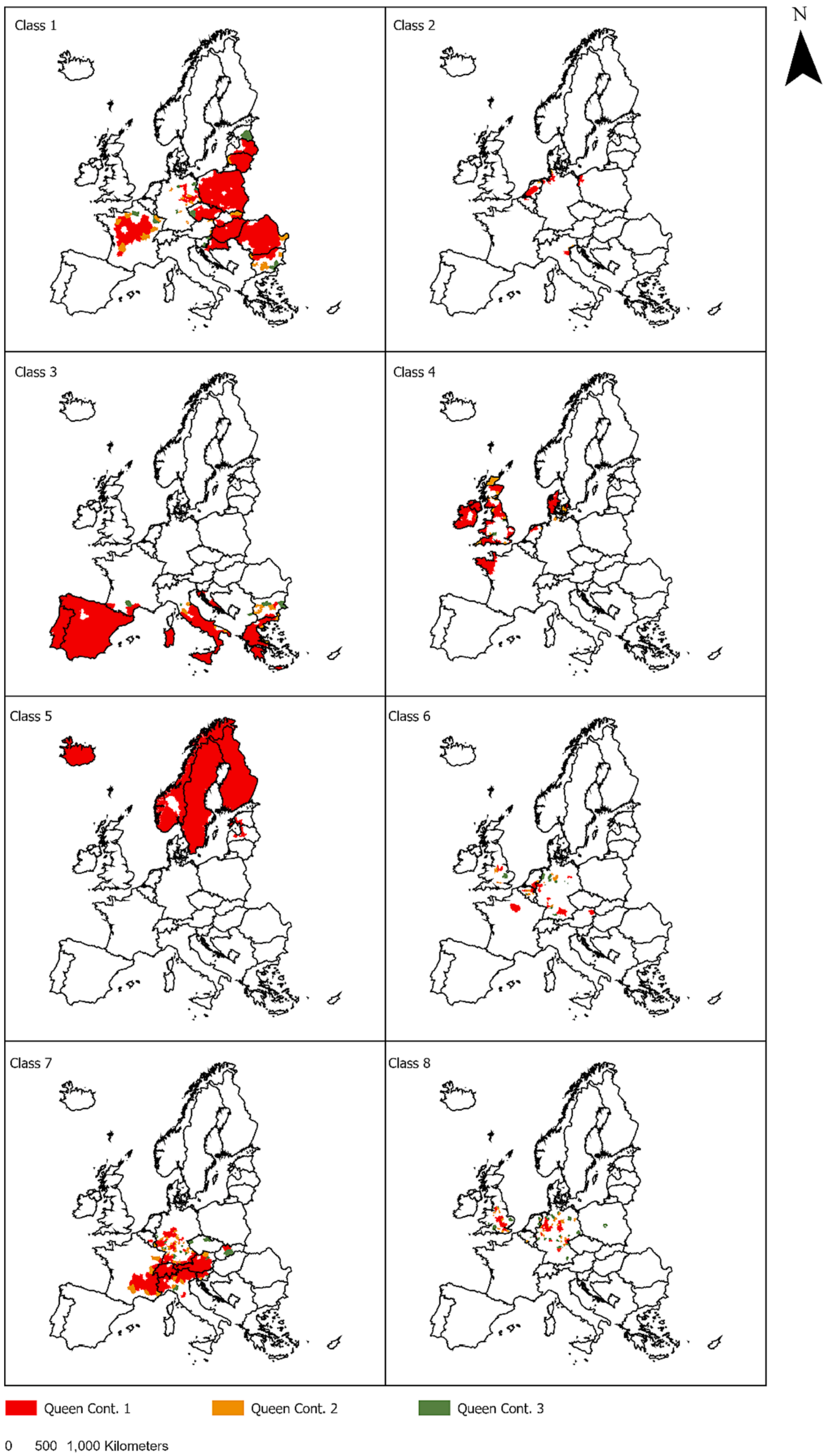

Fig. 9. Distribution of clustering for risk classes (Queen-order contiguity 1–3).

exhibit tendencies towards clustering in the way that was revealed in relation to the class structure. Further work is also needed to explore how the ECRT could be used practically in planning for climate change risk: as a decision-support tool; in helping communicating and raising awareness of the nature of climate change risk facing different places; and in evidencing climate risk through 'hot spot' mapping (de Sherbinin, 2014; Carter et al., 2015; de Sherbinin et al., 2019). This would offer opportunities to explore the 'political' dimensions of data use and analysis in shaping decision-making around climate change risk.

In summary, the paper reports on the development and application of new typology of climate change risk for European cities and regions. In doing so, it offers a direct response to the IPCC and ESPON Climate calls to advance awareness of climate change risks at sub-national levels as part of international efforts to evidence, adapt and respond to climate change risk. The insights revealed by the analysis of the ECRT output have the potential to inform the development of adaptation policy and practice in Europe, particularly at strategic scales, and can support progress towards a climate resilient Europe as envisioned by the European Commission in their EU strategy on adaptation to climate change (European Commission 2021).

CRediT authorship contribution statement

Stephen Hincks: Conceptualization, Methodology, Software, Formal analysis, Validation, Data curation, Writing – original draft. **Jeremy Carter:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – review & editing, Project administration, Funding acquisition. **Angela Connelly:** Conceptualization, Methodology, Data curation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2023.102767.

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